Shocks to Product Networks and Post-Earnings Announcement Drift*

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Abstract: This paper examines whether shocks to less visible product market network peers explains industry level post-earnings announcement drift (IPEAD). On the real-side, we find that peer earnings shocks propagate slowly through the network, creating a complex and conditional autocorrelation structure in earnings shocks. This impacts the financial-side, and IPEAD arises only when shocked peers are less visible in the network and when shocks are driven by persistent supply-side shocks to expenses, and not by demand-side shocks to sales. IPEAD is particularly strong when 10-K expense disclosures are opaque. Collectively, our results suggest that inattention to less visible peers, complex autocorrelation in earnings shocks, and a poor informational environment on the expense side are likely channels that generate IPEAD. IPEAD returns are economically large in subsamples motivated by this explanation.

JEL classification: G14; L22; M41
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Data Availability: All data are publicly available from sources identified in the text.

1. Introduction

The existing literature has documented industry-level price drift following earnings announcement (i.e., industry level post-earnings announcement drift, henceforth IPEAD) using traditional and highly visible industry classifications (Ayers and Freeman 1996; Hui et al. 2013; Hui et al. 2016). While these studies demonstrate that industry earnings shocks impact a focal firm's future earnings growth and stock returns, little is known about the channels that drive the results. It is particularly puzzling that security prices underreact to these publicly observable shocks, and moreover, that industry-wide returns (IPEAD) are more persistent than the firm-specific returns (regular PEAD) (Ayers and Freeman 1996). We fill this void in the literature by advancing a new explanation for IPEAD based on both the visibility of industry shocks specifically on the supply-side of the firm, and the opacity of disclosures explaining the firm's cost structure.

We propose that a highly granular intransitive network model of IPEAD can shed new light on the phenomenon, its propagation through the network, and its underlying sources. We hypothesize and find that IPEAD stock returns only propagate slowly through the network when peers are less visible. Shocks otherwise propagate quickly and predictable stock returns do not arise. Our results are strongest in regions of the network where disclosure is less informative, and earnings shocks are specifically driven by changes on the expense-side (supply-side) of the firm and not on the revenue-side (demand-side). This suggests that although opaque expense disclosures might be optimal to maintain proprietary information about production, this strategy also has potential side effects in the form of inefficient stock prices, which can distort a firm's cost of capital. We thus provide a new explanation of prior research on intra-industry information transfers and IPEAD by illustrating the role of inattention to less visible peers and elevating the importance of supply shocks specifically to expenses, particularly when they are less salient to investors than are demand shocks.

Prior studies have identified industry peers based on the Standard Industry Classification (SICS), North American Industry Classification (NAICS), and Global Industry classification (GICS).[1] Unlike standard industry classifications, which are transitive and vary little over time (Hoberg and Phillips 2010; Lee et al. 2015), dynamic and time varying intransitive networks enable us to examine more precisely how shocks propagate through both near and distant peers, and when propagation is slow or fast. Moreover, the specific network we consider partially overlaps with the aforementioned traditional industry classifications. This allows us to further distinguish earnings propagation through peer relationships that are more visible to investors from those that are less visible using strong comparisons. We are thus able to directly test whether inattention to shocks and opaque disclosures are likely channels generating the slow adjustment in the stock market.

We investigate the impact of peer shocks on a focal firm's earnings growth and stock prices using an important corporate event: earnings announcements. Our joint analysis of visibility and product market distance is made possible through recent advance in textual analysis - the Text Based Industry Classification (TNIC) from Hoberg and Phillips (2010, 2016)[2]. TNIC is a new industry classification that defines industry peers as firms that use common vocabulary in the business description of their 10-K. We use TNIC to first examine how real-side earnings shocks transmit through industry networks. We then examine whether stock market investors efficiently price the impact of peer earnings shocks on a focal firm's earnings surprise.

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[1] We use SIC codes to classify traditional industry peers. We also perform additional analyses later in the paper to confirm that our inferences do not change when we use GICS or NAICS codes.

[2] See Appendix B for further information explaining TNIC measures. The TNIC data is from the Hoberg and Phillips digital library at www.marshall.usc.edu/industrydata.

To ensure that our findings are fully distinct from existing studies that focus on traditional industry classifications, and to further examine the impact of near versus distant peers, we decompose a focal firm's earnings surprise into five orthogonal components: two based on traditional industry (SIC) codes, two based on TNIC industries, and a residual firm-specific component. Because these components are highly correlated in their raw form, we rotate the five components to be orthogonal using a Cholesky decomposition. We find that this adjustment is crucial to separately identify the components of earnings surprises uniquely due to each set of SIC versus TNIC peers, and proximate versus distant peers.

We report several interesting findings. First, on the real-side, we document that economic shocks travel through the network of industry peers with delay, and peer earnings surprises strongly influence a given focal firm's earnings surprise, but with more delay for more distant peers. Specifically, when we divide industry peers into those more closely related to the focal firm and those more distant in each industry network, we find that "close peers" have more persistent and immediate impact on the focal firm.[3] However, more remote peers continue to influence the focal firm earnings with longer delay, suggesting that earnings shocks propagate through the peer network slowly over time. This finding is novel, and shows that network propagation on the real side generates a complex, slow moving, and conditional autocorrelation structure in earnings shocks. Especially in the presence of inattention and opaque disclosure, it is natural to propose that such network behavior can explain the delayed stock market response to industry earnings shocks (IPEAD).

[3] We consider firms sharing the same three-digit SIC or TNIC3 code as "close peers" to the focal firm (TNIC3; SIC3). Similarly, we identify peer firms sharing the same two-digit SIC or TNIC2 code but not the same three-digit SIC or TNIC3 code as "remote peers" (TNIC2⊥3; SIC2⊥3).

Regarding the financial-side, we thus examine whether stock market investors fully internalize this slow propagation of peer earnings shocks on the real side. We first confirm the presence of both own-firm PEAD and IPEAD in our sample, as documented in the existing literature. We then find that IPEAD arising from less visible TNIC network peers is significantly longer lasting and stronger in magnitude than what has been documented in prior research using highly visible traditional peers. Furthermore, TNIC peers subsume the explanatory power of the traditional peers when predicting stock returns. We conclude that no IPEAD underreaction arises in highly visible parts of the peer network once we control for shocks to the less visible nodes in the network.

We further extend the literature by examining the role of network distance and find that the earnings surprises of close peers generate economically larger and more immediate IPEAD than those of remote peers using the standard PEAD announcement windows. However, as we examine longer horizons, distant peers generate growing IPEAD that eventually dominates the slowly decaying signal form close peers. Remarkably the effect of distant peers on returns is delayed as much as a year as the information only slowly propagates through multiple edges of the network. Our stark findings on both visibility and network distance are novel and are not reported in existing studies.

To further understand the mechanism through which IPEAD arises, we decompose earnings surprises into its income statement components. We categorize major items such as sales surprises as shocks to the firm's demand-side. Others such as SG&A and COGS reflect shocks to the firm's supply side. We find that although demand and supply-side shocks both contribute to earnings persistence on the real-side, IPEAD on the financial-side only arises following shocks to the firm's supply-side expenses. We explore the micro-foundation of this novel result and find that IPEAD is strongest when (A) SG&A is important (SG&A is a high fraction of sales), and (B) textual expense disclosures in the 10-K are more opaque. These results indicate that IPEAD has stronger roots in parts of the network where firms have complex and difficult to model expense dynamics that are also economically important drivers of a firm's valuation. We conclude that the market efficiently prices demand shocks, likely because high demand for a firm's products is very salient to investors. In contrast, the market is inattentive to supply shocks in regions of the network where firms disclose less about their expense dynamics.

We also test a number of auxiliary predictions of our inattention hypothesis. We find that IPEAD is particularly large in magnitude (1) when TNIC industry peers are less jointly owned by mutual funds and thus are particularly exposed to inattention (see Cohen and Frazzini 2007) and (2) when the less visible peers are particularly similar to the focal firm and are thus more relevant. Overall, these results support the view that inattention to less visible peers and a poor informational environment surrounding supply-side shocks play a role in explaining IPEAD.

Our key findings are robust. We repeat the analyses using GICS and NAICS codes for traditional industry classifications and find similar results. We also carefully control for price momentum and consider alternative return windows and find that our results continue to be robust.

We contribute to the extant literature in several ways. First, our study adds to the literature on network peer effects by documenting network propagation in earnings on the real-side (Foster 1981; Ayers and Freeman 1997; Pandit et al. 2011; Shroff et al. 2017). Our study is also the first to show that low visibility of peer links is a necessary condition for IPEAD to arise, as we find IPEAD only when we consider less visible regions of the peer network.[4] Furthermore, we provide novel evidence that IPEAD is stronger when shocks are rooted in the supply-side, and particularly

[4] Our study also extends prior research examining the benefits of identifying more informative industry peers (Hoberg and Phillips 2010, 2016; Lee et al. 2015).

in regions of the network where firm disclosures about expenses are opaque. We believe that a highly granular and dynamic intransitive network model of the industry peer network is crucial in understanding how earnings shocks propagate from one peer to another, and when the propagation will create IPEAD.

Our paper proceeds as follows. In Section 2, we review the relevant literature and develop our hypotheses. In Section 3, we provide our research design and data for sample selection. Section 4 contains our empirical results and Section 5 provides the mechanism driving the results. Section 6 provides robustness checks. We conclude our study in Section 7.

2. Literature Review and Hypothesis

2.1. Industry Earnings

Our study is related to research on the firm-specific and industry-wide components of earnings and the pricing of this information. Prior research finds evidence that firm earnings and stock prices are affected by peer firm information. Brown and Ball (1967) show that a significant amount of variation in a firm's earnings can be explained by industry-wide earnings. To offer an explanation for the price drift following earnings surprises called PEAD (e.g., Ball and Brown 1968; Thomas and Bernard 1989, 1990; Livnat and Mendehall 2006)[5], Ayers and Freeman (1997) investigate whether the industry component of earnings is incorporated in stock prices earlier than

[5] PEAD remains robust in recent years and many studies have considered its causes (e.g., Chi and Shantikumar 2016). Earlier work attributes PEAD to investors' failure to appreciate more complex time-series properties of earnings, and a "fixation" on a random walk model with a drift (Bernard and Thomas 1990). Alternative explanations have been advanced to explain PEAD. For instance, Sadka (2006) examines the influence of liquidity risk as a contributing factor to the anomaly. Ng et al. (2008) find that the initial underreaction and subsequent drift is stronger for firms with higher transaction costs, suggesting that market frictions impede price discovery by arbitrageurs.

the firm-specific component. They provide evidence that firm-specific information is the underlying cause of PEAD. However, Elgers, Porter, and Xu (2008) negate Ayers and Freeman (1997)'s assertion after adjusting for measurement error introduced by treating realized returns as unrealized returns.

Recent studies strongly advocate that industry earnings, in part, explain PEAD. Relying on economic theories suggesting that industry earnings are more persistent than firm-specific earnings, Hui et al. (2013) show that investors' underreaction to analysts' forecast revisions is attributable to industry earnings. Relatedly, Hui et al. (2016) find that future stock prices drift in the direction of industry earnings and show that this drift arises from a misunderstanding of the persistence of industry earnings. Kovacs (2016) provides evidence that investors underreact to industry-wide fundamentals based on analysts' forecasts, implying that peer firms' earnings announcements are attributable to PEAD.

Whereas these studies improve our understanding of investor reactions to industry-wide earnings surprises, prior research remains silent about why investors do not correctly price the implications of industry-wide earnings for a firm's earnings growth. This phenomenon is puzzling given that industry-level information is widely available on the public domain and industry-wide earnings are more persistent than firm-specific earnings (Ayers and Freeman 1996). To answer this question, we examine whether shocks to text-based product market peers play an important role in the persistence of earnings shocks and whether IPEAD is driven by these less visible TNIC peers. We also propose a novel mechanism driving these results by examining the role of supply-side shocks to TNIC peers and information opacity of 10K- disclosures regarding supply-side shocks.

2.2. Product Market Networks

Firms have many economic links to other firms through various types of relationships. The literature provides evidence that investors use peer firm information to infer the fundamentals about the focal firm. In addition to earlier work on intra-industry information transfer (e.g., Foster 1981), recent studies examine the effect of disclosures made by industry peers on real decisions of a focal firm (Badertscher et al. 2013), or the circumstances under which such an effect becomes more salient (Shroff et al. 2017). Shroff et al. (2017) show that the effect of peer disclosures becomes more evident when information about the focal firm is more scant, and that peer information is substituted for focal firm information when focal firm disclosure increases.

Among the many types of relatedness networks, those based on the product market have been of particular interest in the literature. Ahern and Harford (2014) emphasize the importance of vertical relationships in the product market in explaining merger waves. They find that M&A deals propagate through peer links in the supply chain, and that the transmission of merger waves depends on the distance in the supply chain. The literature also documents that horizontal links or technological links can influence mergers and acquisitions (Harford 2005; Hoberg and Phillips 2010; Bena and Li 2014; Sheen 2014). Whereas much past research has focused on investment and mergers, we focus on the ability of product market relationships to explain the propagation of earnings surprises on the real-side and abnormal price drift on the financial stock market-side.

2.3. Hypothesis Development

We propose that earnings surprises from text-based product market peers have strong and persistent implications for future earnings because TNIC identifies economically relevant peers that are missed in traditional industry classifications. We also consider the distance in the product market between firm pairs to test for network propagation in industry earnings surprises. Because the economic influence of industry peers increases with relatedness within an industry boundary (Ahern and Harford 2014), we anticipate that earnings shocks to closely connected peers have a more immediate effect on the focal firm's earnings than do earnings shocks to remotely connected peers. We formalize our real-side hypothesis as follows:

H1: Earnings surprises of text-based product market peers will have more persistent impact on future earnings than traditional industry peers. Additionally, more closely connected peers will have stronger and more immediate impact on the focal firm's earnings.

To the extent that the stock market does not efficiently price information from less visible firms (e.g., Hirshleifer and Teoh 2003), we expect stronger price drift following shocks to TNIC product market peers relative to traditional industry peers. TNIC industries were first introduced to the literature near the end of our sample by Hoberg and Philips (2010, 2016). Moreover, they were not published in any material distributed widely to investors as was the case for traditional SIC industries. Hence TNIC links were subjected to less attention by investors during our sample period (Hoberg and Phillips 2017). In contrast, SIC industry links are widely used and reported to investment professionals and academics since 1937. As was the case for the real-side, we anticipate greater and more immediate financial-side stock price reactions following shocks to more relevant proximate peers. However, we expect that more distant peers might impact the focal firm with delay, as shocks take time to propagate greater distances through the peer network.

As inattention and underreaction are unique consequences of investor decisions, our predictions on the financial-side differ sharply on this dimension from those on the real-side. In particular, our inattention hypothesis predicts that the market will fully price shocks to highly visible peers, but will not fully price shocks to less visible peers. Yet inattention will not materially affect results on the real-side, which is not influenced by the attention of stock market investors.

Our central financial-side prediction is that only shocks to less visible peers will influence stock returns:

H2: Investors are more likely to underreact to earnings surprises to less visible TNIC product market peers than traditional industry peers. Additionally, investors are more likely to incorporate earnings surprises to more distant peers after significant delay.

The aforementioned hypotheses derive from characteristics of the entire product market surrounding a given firm. We also consider whether specific accounting information can amplify these predictions. Earnings, being the last item on the income statement, can be influenced by a host of different shocks, each having different implications for future earnings and investor attention. We expect that investors will most efficiently price shocks characterized by a rich informational environment, and in contrast, they are less likely to impound shocks from opaque origins into stock prices.

The informational environment surrounding a firm's demand-side is likely richer than that surrounding its supply-side. Investors consider sales to be the most important financial data and thus sales information is the most frequent disclosure category in management's guidance (Lansford et al. 2008). Attention to the demand-side is also a function of the appeal of the firm's product offerings, which are salient as firms have strong incentives to increase product awareness and promote their products. In fact, investors are often buyers of these same products.

However, it is less straightforward for investors to understand cost behavior on the supply-side. Firms' production technology is often protected by trade secrets and supply-side information is often proprietary. It is natural that firms have strong incentives to withhold information on their plans and accomplishments on the supply-side due to the threat of losing competitive advantage (Healy and Palepu 2001; Guo et al. 2004; Koh and Reeb 2015). To the extent that competitors might benefit from these disclosures and expropriate unprotected secrets, firms are more likely to withhold such disclosure, making the informational environment on a firm's supply-side more opaque than its demand-side. We consider the following hypothesis:

H3: Investors are more likely to underreact to earnings surprises that are driven by shocks to the firm's cost structure on the supply-side than they are to shocks to the demand-side. This prediction is amplified when firms have higher costs and when their expense disclosures are more opaque.

3. Research design

3.1. Firm and Industry SUE

Consistent with prior studies (Bernard and Thomas 1989; Ball and Bartov 1996; Sadka 2006), we define SUE based on a seasonal random work model. As an improvement to using analyst forecasts as expected earnings to define SUE, the use of a seasonal random walk model minimizes the attrition of sample firms included in our analyses. First, we take the seasonal difference as a measure of unexpected earnings ($UE_{it} = EARN_{it} - EARN_{it-4}$). We then standardize this measure by subtracting the mean of the unexpected earnings over the past eight quarters, and then dividing by the standard deviation of the unexpected earnings over the past eight quarters.

$$SUE_{it} = \frac{UE_{it} - \mu_{it}}{\sigma_{it}} \qquad (1)$$

where μ_{it} is the mean of unexpected earnings from t-1 to t-8, and σ_{it} is the standard deviation of unexpected earnings from t-1 to t-8.

To examine relatedness of both near and distant product market peers, we divide these peer firms into two categories based on their product descriptions as depicted in Figure 1 (Hoberg and Phillips 2010; 2016). Among the total set of possible peers, those that are most closely related belong to a firm's TNIC3 industry. These firms satisfy a roughly 2% granularity distance from the focal firm.[6] This classification defines industry peers as all firm pairs with textual similarity in the highest 2% among all firm pairs in each year. TNIC peers overlap materially but not completely with SIC-based peers. Among peers are in the same SIC3 for example, 43.8% are also in the same TNIC3 industry. If two peers are in the same TNIC3, 49.8% are in the same SIC3. TNIC2 includes all peers in TNIC3, and also includes the broader set of closest peers up to the broader 5% granularity.[7] TNIC3 and TNIC2 are thus analogous to three-digit SIC codes (SIC3) and two-digit SIC codes (SIC2) in terms of granularity, respectively. The former captures the narrower set of close peers, where the latter captures a broader set of peers including more distant peers. We denote peer firms located within TNIC2 ("Outer circle") but outside of TNIC3 ("Inner circle") as TNIC2⊥3. These are the set of distant peers. Analogously we denote SIC2⊥3 as the set of more distant peers that belong to the SIC2 classification but not the SIC3 classification. To construct industry earnings shocks, we compute the mean value of firm-specific earnings shocks (SUE_{it}) across all firms included in a given industry group and denote them as $SUE_{TNIC,t}$ and $SUE_{SIC,t}$. When there exists only one firm in a given industry (i.e., monopolistic firms), the industry shock variable is set to zero.

Due to the fact that these firm and industry components of earnings surprises are highly correlated, multicollinearity among these variables may confound our inferences if we use these variables in regressions in their raw form. To address this issue, we conduct the inverse Cholesky decomposition, which transforms a set of correlated variables into a set of uncorrelated variables (See Appendix C for details). Specifically, the inverse Cholesky decomposition converts a set of

[6] This granularity is chosen to calibrate TNIC3 to have granularity equal to that of SIC3. See Hoberg and Phillips (2016) for details.
[7] This granularity calibrates TNIC2 to be as granular as SIC2.

K correlated variables into K uncorrelated variables, where each of the K variables has a corresponding unique "primitive signal" resulting from the decomposition. The decomposition is meant to preserve all information in the K variables, and to rotate the variables such that each variable's signal is separated from the others. As expected, we observe that before the inverse Choleksy decomposition, raw SUE variables are indeed highly correlated (these correlations are as high as 0.562). In contrast, the adjusted SUE variables treated with the Cholesky adjustment are essentially uncorrelated.

[Insert Figure 1 Here]

3.2. Regression Models

To examine earnings persistence and network propagation effects on the real-side, we implement the inverse Cholesky decomposition and regress ex post firm-specific SUE on the ex ante TNIC and SIC industry SUE components along with the ex ante firm-specific SUE component. The coefficients on the five independent SUE variables represent the unique persistence of firm and various industry earnings surprises. Although firm-specific SUE is not related to a network effect, we include this variable for completeness and to explicitly control for the well known autoregressive property of firm earnings. We predict that the persistence of less visible TNIC earnings surprises should be greater than those from more visible SIC industry peer earnings surprises. In addition, we predict that earnings surprises from close-in peers (TNIC3; SIC3) should be more persistent than those from remotely connected peers (TNIC2⊥3; SIC2⊥3). We specifically consider the following model to test our real-side hypothesis:

$$SUE_{i,t+1} = SUE_{i,t} + SUE_{TNIC3,t} + SUE_{TNIC2\perp3,t} + SUE_{SIC3,t} + SUE_{SIC2\perp3,t} + Size_{i,t} + BTM_{i,t} + \varepsilon_{i,t}, \tag{2}$$

where i and t denotes firm and year quarter, respectively. Following prior research, across all regressions, we include firm size and the book-to-market ratio to control for risk characteristics, and we cluster standard errors by firm and quarter.

To investigate whether investors efficiently price the implications of peer firm surprises for focal firm earnings growth, we test our financial-side hypothesis by replacing future SUE with the focal firm stock return in the regression model. In particular, we regress ex post style-adjusted (cumulative size and book-to-market adjusted) returns on all five SUE variables (Livnat and Mendenhall 2006; Chi and Shantikumar 2016).[8] Firms belong to one of 25 (5x5) style portfolios depending on their size and book-to-market ratio each year. We compute abnormal returns by subtracting the value weighted portfolio returns of stocks in each bin from each firm's raw returns. CAR[X,Y] denotes abnormal returns accumulated over a window from X calendar days to Y calendar days after the earnings announcement. We use abnormal returns accumulated over a quarter (CAR[2,90]) as our baseline specification consistent with the existing literature. To further examine the extent to which stock prices incorporate information in earnings shocks to the various firm and industry components, and to test for slower moving network propagation effects, we accumulate abnormal returns over various windows up to two years after earnings announcements. This is also motivated by the implication of inefficient markets that more severe underreaction should generate longer lived return predictability. We estimate the following model[9] to examine the pricing of firm specific and industry earnings surprises:

$$\begin{aligned} CAR_{i,t+1} = SUE_{i,t} + SUE_{TNIC3,t} + SUE_{TNIC2\perp 3,t} + SUE_{SIC3,t} + SUE_{SIC2\perp 3,t} \\ + Size_{i,t} + BTM_{i,t} + \varepsilon_{i,t} \end{aligned} \tag{3}$$

[8] Our results are similar when we use size-adjusted returns as our dependent variable.
[9] Including momentum, defined as monthly cumulative returns from t-13 to t-2 as an additional control on the financial-side does not alter our inference.

where i and t denotes firm and year quarter, respectively. In this regression, the coefficient on firms' own SUE indicates the return drift following own firm earnings announcements. Similarly, the coefficients on the industry SUE terms identify the return drift following earnings shocks to industry peer groups.

3.3. Sample and Descriptive Statistics

Our initial sample includes firm quarters listed in the intersection of the COMPUSTAT and CRSP for the years 1999 to 2011. After requiring data to be present in the 10-K based TNIC database of product market peers, we obtain 202,488 firm quarter observations. Finally, for the market reaction tests, we also require non-missing return data accumulated up to four quarters after earnings announcements. We winsorize variables at the 1 and 99 percentiles to mitigate the effect of outliers.

Table 1 provides descriptive statistics for the variables used in the regression tests. The mean values for our CAR variables are close to zero, indicating that our size and book-to-market adjusted returns are properly constructed for all windows.[10]

[Insert Table 1 Here]

Table 2, Panel A provides Pearson correlations between our SUE variables after the inverse Cholesky decomposition is applied, and the one quarter baseline market reaction CAR[2,90].[11] Consistent with prior research (Bernard and Thomas 1989, 1990), the focal firm's own earnings surprise is positively related to the ex post abnormal return. We also document that this price drift is positively related to TNIC industry peer shocks. In contrast, it is only weakly positively related

[10] All our variables are defined in Appendix A.

[11] We also repeat the analysis using various windows such as CAR[2,180] and CAR[2,360] and find that our inferences are similar.

to SIC3 industry peer shocks, and negatively related to more distant SIC peers. These results confirm that IPEAD is strong in our sample and that it is only strongly driven by less visible text-based peers. TNIC industry peers' earnings shocks thus correlate more with ex post abnormal returns than SIC industry peer shocks. This conclusion holds both for closely connected and remotely connected TNIC and SIC peers, respectively. Panel B of Table 2 shows that the correlation between the top line of income statements and supply side items, namely COGS and SG&A, is very high and significant - a fact that will be relevant later when we need to separate demand and supply side shocks.[12]

[Insert Table 2 Here]

4. Results

4.1. Results of the Real-Side Tests

We test our real-side hypothesis regarding the relation between shocks to product market peers and a focal firm's earnings surprises in Table 3.

[Insert Table 3 Here]

We find that the coefficients on SUE_{TNIC3} are significantly positive in predicting the focal firm's ex post earnings surprise. Moreover, this coefficient is substantially larger than the SUE_{SIC3} coefficient. However, as we predicted in our real-side hypothesis, the SUE_{SIC3} coefficient still does contain residual information. This result is consistent with Hoberg and Phillips (2016), who find that although TNIC peers are more informative than SIC peers, both peer groups do contain some

[12] It is noteworthy that Peters and Taylor 2017 suggest that in 90% of firms, Compustat includes R&D in SG&A, implying that R&D is an important determinant of SG&A.

significant information. These results overall suggest that earnings surprises from shocks to TNIC peers have a more persistent effect on the focal firm's earnings surprises than do shocks to SIC industry peers. We also find similar results for remotely connected peers that reside outside a focal firm's "inner circle" of rivals but reside inside the "outer circle". It is noteworthy that $SUE_{TNIC2\perp3}$ significantly predicts future earnings while such predictability is not found for $SUE_{SIC2\perp3}$, suggesting that more distant traditional SIC industry peers contain little information relevant to predicting a focal firm's earnings surprises. These results further support our hypothesis (H1) regarding differential persistence in industry earnings surprises. Also as expected, we find that more closely connected industry peers have more persistence than do more remotely connected industry peers. In particular, the coefficients on SUE_{TNIC3} (SUE_{SIC3}) are greater than those of $SUE_{TNIC2\perp3}$ ($SUE_{SIC2\perp3}$). This supports our hypothesis that product market distance also matters in explaining the persistence of earnings surprises.

A final result in Table 3 is that, as we use deeper lags, the $SUE_{TNIC2\perp3}$ coefficient decays more slowly than the SUE_{TNIC3} coefficient, consistent with slower propagation of shocks from more distant peers. However, we note that this is difficult to see by simply looking at the coefficients in Table 3, and hence we plot the decay patterns of the various coefficients in Figure 2. Panel A of Figure 2 plots the Table 3 coefficients for various lags of SUE_{TNIC3} and SUE_{SIC3}, where each coefficient is scaled by the most recent quarter's coefficient so that the decay is measured relative to the largest initial value. The figure thus shows the rate of decay of the initial persistence level over time. For example, a value of 0.50 in the second quarter would indicate that half of the signal decays after two quarters. We find that although TNIC3 is substantially more persistent than is SIC3, both signals decay at a nearly identical rate. This remarkable finding is likely explained by the fact that TNIC3 and SIC3 are calibrated to have exactly the same granularity, and hence we would predict a similar decay rate even though TNIC3 is more informative than SIC3 in terms of raw impact.

Panel B of Figure 2 shows that the decay rate of more distant peers is slower than that of close-in peers. This indicates that it takes more time for earnings surprises from more distant peers to propagate through the network to the focal firm. For example, after three quarters, the TNIC3 coefficient decays to 39.7% of its original value. In contrast, the more distant TNIC2⊥3 decays to 62.8% of its original value. The latter is 60% larger than the former, indicating a very strong relationship between the decay rate and product market distance. We conclude that more distant industry shocks propagate through the network of industry peers with greater lag than do shocks to more close-in industry peers.

[Insert Figure 2 Here]

Taken together, the results of Table 3 and Figure 2 are consistent with the notion that product market peer earnings (TNIC) are more informative about own firms' future earnings than traditional SIC-based industry earnings. Moreover, shocks to more distant peers have less initial impact, but their longer term impact on the focal firm decays more slowly over time. If investors are not fully aware of these nuanced stochastic properties, then these findings have important implications for the financial-side.

4.2. Result of the Financial-Side Tests

To test whether our findings on the real-side mirror stock return drifts following earnings announcements on the financial-side, we examine the link between our ex ante firm-specific and industry-wide components of SUE and ex post abnormal returns. In Table 4, we estimate equation (3) separately for the overlapping and non-overlapping windows. In Panel A of Table 4, we first confirm that the coefficient on the focal firm's earnings surprise is positive and significant in all columns and that the magnitude of the coefficients increases as we measure returns over longer periods of time. This pattern is consistent with the notion that investors exhibit underreaction to earnings surprises for several quarters (PEAD). More importantly, Panel A shows that the coefficients on earnings surprises from TNIC peers are positive and significant. In contrast, we do not find significant coefficients for traditional industry peers (SIC3; SIC2⊥3), implying that investors fully account for the implications of the earnings surprises to more visible SIC industry peers. These results suggest that the price drift associated with industry shocks (IPEAD) is primarily driven by less visible TNIC product market peers.

The return drift associated with closely connected product market peers illustrates that IPEAD is economically relevant in our sample. This impact also increases as we extend the return window up to a full year. In total, a firm with a one standard deviation shock to its TNIC3 peers experiences a stock return that is 1.8% higher in the following year. This result is economically large, and it understates the even larger returns available in quintile or decile portfolios.

We next discuss the impact of more distant TNIC2⊥3 peers on IPEAD. Although shocks to more proximate TNIC3 peers generate IPEAD immediately in the next quarter, shocks to more distant peers only generate significant IPEAD over longer horizons such as one year in Panel A. In other words, investors' reaction to the earnings surprises of TNIC2⊥3 peers is more lethargic than their reaction to the earnings surprises of more proximate peers. This finding indicates that shocks to more distant peers propagate through the network to the focal firm with delay. These propagation results are similar to those of Ahern and Harford (2014), who find network propagation effects for vertical mergers in the supply chain.

[Insert Table 4 Here]

In Panel B of Table 4, we also examine abnormal returns defined over non-overlapping windows to more uniquely identify the incremental return drift attributable to each period, and to more rigorously illustrate the differential impact between near and proximate peers. We find significantly positive results on the closely connected product market peers in columns (1) and (2) for short horizons. These results indicate that investors delayed response to proximate peers lasts a full year, although the rate of return accumulation decreases with time. In the second quarter after the earnings announcement (column (2)), we find that the magnitude of the delayed response with respect to SUE_{TNIC3} is comparable to that of firm-specific SUE, supporting the economic importance of this variable in explaining IPEAD.

Panel B of Table 4 also shows that when more distant TNIC2⊥3 peers are shocked, the market reaction is particularly lethargic. Unlike other variables, where coefficients imply declining impact on returns over time, we find that the impact of these more distant peers actually increases over time and becomes significant in the one to two year horizon. This result is particularly supportive of the hypothesis that shocks to more distant peers propagate through the network to the focal firm with material delay.

Overall, the evidence in Table 4 is consistent with our hypothesis (H2) that investors react slowly to industry earnings shocks with less visibility (i.e., inter-firm relations in the product market), and this significantly contributes to IPEAD. Delays are particularly long when peers are more distant in the product market.

5. Mechanisms

In this section, we examine the inattention hypothesis and mechanism in greater detail. Because less visible TNIC industry shocks subsume traditional SIC-based peer shocks in our earlier tests, the analysis in this section focuses only on TNIC peers for parsimony.

5.1. Supply-Side Shocks

We first consider the differential impact of demand and supply side shocks on earnings surprises. Prior research suggests that a firm's revenue shocks (demand-side) are more persistent than expense surprises (supply-side) (Ertimur et al. 2003). We decompose industry earnings surprises into these components by first examining surprises to each item on the income statement that contributes to earnings. We specifically examine TNIC peer surprises to revenues (Sales), operating income before depreciation (OIBDP), operating income (OI), and pre-tax income (PI). We examine which ex ante line item surprises are associated with a focal firm's ex post real-side earnings surprises and its subsequent price drift. Table 5 reports the results. We find that all line item surprises are significantly related to a focal firm's earnings surprise. Consistent with prior research showing greater persistence of revenue shocks (Livnat 2003), we find that TNIC peer revenue shocks are particularly important.

We next examine whether these ex ante line item surprises are impounded in stock prices. We find that these shocks do not predict IPEAD, suggesting that investors efficiently incorporate peer revenue shocks into stock prices. In contrast, investors do not fully price TNIC3 surprises to line items that are lower down on the income statement including OIBDP, OI, and PI. These results suggest that investor underreaction to peer earnings shocks is likely to arise from shocks to the supply-side, as these line items are differentiated from sales growth shocks primarily due to their inclusion of the firm's expenses. The magnitude of coefficients for OIBDP, OI, and PI suggests that approximately 80 to 90% of total IPEAD is attributable to supply-side expense shocks.

[Insert Table 5 Here]

To further explore this link to the expenses, we proceed to define supply- and demand-side shocks directly. We partition earnings surprises into a demand-side shock and an orthogonal supply-side shock and repeat the analysis reported in Table 5. We first note that raw (SG&A + COGS), which we define as "SupSide", is highly correlated with raw sales with a Pearson correlation of 0.984. This is expected, as for instance, if sales double, the firm needs to make twice the goods, and hence COGS should roughly double. Note that this will occur even if there are no shocks to the firm's cost structure. To evaluate shocks unique to the cost structure itself, we thus need to identify major changes in costs that are not driven by mechanistic changes in sales. We thus regress total costs (COGS+SG&A) on sales and take the residual, which we name "ResSupSide". This identifies supply-side shocks that are uncorrelated with demand-side shocks. We next examine if these unique supply-side shocks can explain IPEAD.

We report the results in Table 6. As shown in Panel A of Table 6, we first find that both ex ante demand and supply shock components are significantly related to a focal firm's future earnings surprises on the real-side. Consistent with our findings in Table 5, we also find that the coefficient on $DemSide_{TNIC3}$ is greater than that of $ResSupSide_{TNIC3}$. This implies that unexpected demand shocks are more important than unexpected supply shocks in predicting a firm's future real-side earnings surprises. However, although they are weaker than demand-side shocks, we still find that $ResSupSide_{TNIC3}$ is highly persistent in its unique ex post impact on the focal firm. Hence, to be efficient, the stock market would need to price the impact of both demand and supply-side shocks on a focal firm, as both materially predict the focal firm's future earnings.

We thus test whether the market efficiently prices both demand and supply shocks and examine abnormal returns over various windows. As reported in Panel B, Table 6. We find that

IPEAD arises from the supply-side shocks. Specifically, we find that the coefficient on $ResSupSide_{TNIC3}$ is positive and significant whereas the coefficient on $DemSide_{TNIC3}$ is insignificant. This evidence suggests that mispricing relating to IPEAD is driven by supply shocks to TNIC peers.

[Insert Table 6 Here]

5.2. Inattention

Consistent with our investor inattention hypothesis, we have shown that less visible TNIC peers generate IPEAD whereas more visible SIC peers do not. We examine if our strong results on the supply-side, but not the demand-side, might also be driven by investors' inattention. It likely that investors pay more attention to the demand for a firm's products to extrapolate sales growth because a firm's future sales and its growth would be a key determinant of firm valuation. By contrast, they might be less informed about cost structures such as marketing expenses and R&D expenses given that firms have incentives to limit disclosure of information about cost structures due to competitive threats.

To provide corroborating evidence about the mechanism driving IPEAD, we first examine how quickly stock turnover adjusts around supply-side and demand-side shocks. Figure 3 plots the difference in scaled turnover for firms that receive large positive shocks relative to those that receive large negative shocks (we separately display supply-side and demand-side shocks). Scaled stock turnover is the natural log of monthly turnover (share volume traded/shares outstanding) scaled by average stock turnover from months t-13 to t-2.

Figure 3 shows that turnover increases earlier and more efficiently around demand-side shocks relative to supply-side shocks. For example, 65% of the total increase in turnover has already occurred by the month zero (the month of the shock) for demand shocks. This is about

52.5% for supply-side shocks. More important, 22% is already realized three months before the shock for demand-side shocks, and this is only 6% for supply-side shocks. In all, these findings reinforce the notion that investors pay less attention to supply-side shocks and this inattention translates to large ex post return predictability.

[Insert Figure 3 Here]

Because IPEAD should only be important for those firms with high expenses, we also expect that SG&A expenses and opaque expense disclosures will further amplify the delayed response to supply shocks. To further support the view that the investor attention drives the drift associated with the supply-side, we examine whether investors' lagged reaction to supply-side news is larger when firms have high SG&A and when expense disclosures are opaque. In Table 7, we present the results.

We first partition the sample into quintiles based on each firm's SG&A (Selling, General and Administrative) to sales ratio and examine the magnitude of IPEAD for the lowest and highest SG&A quintiles. Panel A of Table 7 shows that the TNIC3 coefficient is positive and significant only in the highest quintile group. This further supports our conclusion that investors do not fully price information embedded in SG&A. We also partition the sample based on COGS and find that the coefficients are positive and significant in both the highest and the lowest quintiles. Hence our findings indicate that investors particularly underreact to SG&A shocks.

To examine the role of disclosure opacity, we construct a text-based measure of expense disclosure opacity similar to Hanley and Hoberg (2010) and relate it to IPEAD. Specifically, we identify MD&A paragraphs as expense-related when they use the words "expense" or "expense". We then compute the cosine similarity between each firm's expense paragraphs and the average expense vocabulary across all firms in the given year.

The resulting measure is bounded in [0, 1], and a higher number indicates that expense disclosures are more opaque. Intuitively, this would indicate that the firm's disclosure resembles the average disclosure across all firms, indicating excessively general or vague disclosure. Lastly, because we seek to identify firms that are more opaque on the supply side than on the demand side, we divide the text-based expense opacity measure by a similar opacity measure based on revenue disclosures (based on MD&A paragraphs using the words "revenue", "revenues", and "sales").

Panel B of Table 7 shows the results from this analysis. Using the text-based opacity measure, we partition the sample into quintiles in each year. We find that the coefficients on SUE_{TNIC3} is larger for the most opaque quintile and the difference between the high and low quintile coefficients is also statistically significant at the 1% level. We find similar results in the extended return windows.

To ensure the Panel A and B results are distinct, we sort our sample into two dimensions: SG&A and expense opacity[13], and examine whether this result is most pronounced for firms with high SG&A and high expense opacity. As expected, we find that the coefficients on SUE_{TNIC3} are larger and more significant in firms with high SG&A and high opacity scores. Results for $SUE_{TNIC2\perp 3}$ mirror the results from SUE_{TNIC3}. The results reinforce the notion that our findings are primarily driven by investors' delayed response to supply-side shocks, particularly when disclosure is opaque.

[Insert Table 7 Here]

To further investigate the role of inattention, we consider mutual fund common ownership of peer firm pairs (see Cohen and Frazzini 2008). Cohen and Frazzini (2008) suggest that when

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[13] In two-way sorting, we partition into terciles to ensure a sufficient number of observations in each group.

many mutual funds commonly own a given pair of stocks, then it is likely that the specific economic link between the pair has a high level of attention. They consider this test of inattention specifically to vertical customer and supplier economic links. We apply this test to the horizontal TNIC links considered in our study.

To implement this test, our initial unit of observation is a firm pair. For each such pair, we measure the intensity of mutual fund joint ownership of both stocks in each pair. We then average this quantity over all permutations of firm pairs in each TNIC industry peer group and thus obtain joint ownership metrics for each individual firm's industry peers in each year. Industry peer groups with higher joint ownership are subjected to greater investor attention, and a consequence is that investors should be more aware of the economic links between such linked firms. We then sort firms into quintiles in each year based on the intensity of mutual fund joint ownership of the focal firm and its peer firms.

Table 8 reports the results. We find that the market reaction to TNIC3 shocks becomes significant starting from the CAR[2,90] window for the lowest quintile of joint ownership. In contrast, we find no significant IPEAD in the highest quintile. In the longer CAR[2,180] and CAR[2,360] windows, we also observe that the magnitude and significance of IPEAD is strong and pronounced for the lowest joint ownership quintile, whereas the corresponding figure for the highest quintile is marginally significant at the 10% level. These results support the investor inattention hypothesis. We also find some evidence that investors exhibit a delayed response to the earnings surprises of more visible industry peers (SIC industry) in the lowest quintile. This is further consistent with limited attention and processing power (Hirshleifer and Teoh 2003; Cohen and Frazzini 2008; Menzley and Ozbas 2010).

[Insert Table 8 Here]

A final prediction in our framework is that two ingredients are both needed for IPEAD to be strong: inattention and strong economic links. Our use of TNIC peers is relevant on both dimensions, as existing work illustrates that TNIC links are stronger than traditional SIC links, and also that TNIC peers are less visible. However, we further predict that IPEAD should be even stronger when TNIC peers are particularly proximate (similar) to the focal firm. The relevance of shocks to these peers is very high, and if investors are inattentive to shocks to these peers, we predict more pronounced IPEAD. Using TNIC based product similarity measures from Hoberg and Philips (2016), we partition our sample into quintiles based on TNIC total similarity (the sum of text-based similarity scores between a focal firm and all of its TNIC3 peers) and then examine the magnitude of IPEAD in the highest and lowest quintiles.

Table 9 reports the results. The table shows a significant delayed market response to the earnings surprises of TNIC3 peers in the highest total similarity quintile but we do not find any evidence in the lowest quintile. We also find that the return drift associated with focal firm earnings surprises is greater in the highest quintile than in the lowest quintile across all columns. The magnitude of the delayed response to the earnings surprises of TNIC3 peers is also greater than the earnings surprise of the focal firm itself. In other words, IPEAD is significantly greater in markets with higher total product similarity. Overall, the results in Table 9 indicate that shocks to highly proximate peers that are also less visible generate particularly strong IPEAD.

[Insert Table 9 Here]

6. Additional Tests

Although Standard Industry Classification (SIC) codes have been widely used in the literature, we also examine whether our results are robust to alternative industry classifications including Global Industry Classifications Standard (GICS) codes and North American Industry Classification System (NAICS) codes.

Table A1 in the online appendix presents results for earnings persistence using GICS instead of SIC codes. Consistent with our findings, we find that earnings shocks to TNIC peers have a larger effect on a firm's earnings surprises than do earnings surprises to GICS industry peers. Table A2 reports that IPEAD drift results when TNIC is compared to GICS industry peers. We continue to find a large drift associated with TNIC earnings shocks. Moreover, we find no drift associated with GICS earnings shocks. These results indicate that IPEAD is mainly driven by shocks to less visible peers alone and reinforces our findings based on traditional SIC codes. We also consider tests based on NAICS codes. Table A3 and Table A4 show the results. We continue to find a significant difference in persistence between TNIC peers and NAICS peers and once again the drift is largely associated with less visible text-based TNIC industry peers. These tests provide added robustness confirming that the drift associated with industry-wide earnings news is driven by less visible TNIC peers.

We also control risk alternatively by using size-adjusted returns and including momentum as an additional control in the market-side regressions. Consistent with the main results, Table A5 shows that industry-level price drift following earnings announcements occur only from the less visible TNIC peers and that investors needs more time to incorporate shocks to distant peers. Using momentum defined as accumulative stock returns from month t-12 to t-2, Table A6 reports qualitatively similar results. Lastly, Table A7 extend the return window used in the univariate test to [2,180] and [2,360]. The results closely resemble those in Panel A of Table 2. TNIC peers have stronger and larger correlation coefficients with the return measures, and within TNIC peers, the correlation of close peers is stronger than that of remote peers.

7. Conclusion

We use a dynamic network approach to examine whether shocks to less visible product market peers play an important role in the persistence of earnings shocks on the real-side and the stock market pricing of earnings shocks on the financial-side. The underlying premise of our analysis is that inattention to industry shocks, complexity in the autoregressive properties of earnings shocks, and an opaque informational environment are likely channels driving slow price adjustment in the stock market.

To test our conjecture, we separately consider ex ante shocks to less visible text-based TNIC peers and to highly visible SIC industry peers. As expected, earnings shocks to either set of peers predict future focal firm earnings on the real-side. However, only less visible TNIC product market peers generate significant IPEAD on the financial-side. Further reinforcing these effects on both the real and financial-sides, we also find novel network propagation results, as ex ante shocks to more distant peers propagate through the peer network to a focal firm with increasing delay as long as one year. These results together suggest that inattention to less visible peers is a necessary condition for IPEAD to become large, and complexity in the autoregressive properties due to heterogeneous network distances can exacerbate these effects. We further show that comparisons between text-based industry peers and alternative industry peers based on GICS and NAICS provide similar robust results.

To gain further insight into the mechanism driving our results, we explore how shocks to peer sales (demand-side shocks) differentially impact our results as compared to shocks to peer expenses (supply-side shocks). We find that the market is particularly slow to price supply-side shocks to less visible peers, particularly when the level of SG&A expense is high and the firm's textual 10-K expense disclosure is opaque. Additional tests suggest that investors are attentive to salient demand shocks, but they are inattentive to shocks that uniquely impact a firm's cost structure. Such cost-side shocks are likely to generate less attention from investors as firms have strong incentives to shield information about their cost advantages from rivals.

Finally, our results are also stronger when industry peers are less jointly owned by mutual funds, and when product similarity among TNIC peers is high. Collectively, we provide evidence suggesting that investor inattention and poor information environments surrounding supply-side shocks can explain why IPEAD arises. Our results also suggest that network propagation models have excellent potential in modeling the dynamics of earnings shocks through relatedness networks over time. This is particularly the case when relatedness, attention and opacity can be measured in a continuous way.

References

Ahern, K. R., and J. Harford. 2014. The importance of industry links in merger waves. *The Journal of Finance* 69 (2): 527-576.

Ayers, B., and R. N. Freeman. 1997. Market assessment of industry and firm earnings information. *Journal of Accounting and Economics* 24 (2): 205-218.

Ayers, B. C., O.Z. Li, and P. E. Yeung. 2011. Investor trading and the post-earnings-announcement drift. *The Accounting Review* 86 (2): 385-416.

Baginski, S. 1987. Intra-industry information transfers associated with management forecasts of earnings. *Journal of Accounting Research* 25 (2): 196-216.

Ball, R., and P. Brown. 1968. An empirical evaluation of accounting income numbers. *Journal of Accounting Research* 6 (2): 159-178.

Ball, R., and E. Bartov. 1996. How naive is the stock market's use of earnings information? *Journal of Accounting and Economics* 21 (3): 319–37.

Bena, J. and K. Li. 2014. Corporate innovations and mergers and acquisitions. *The Journal of Finance* 69 (5): 1923–1960.

Bernard, V. L., and J. K. Thomas. 1989. Post-earnings-announcement drift: Delayed price response or risk premium? *Journal of Accounting Research* 27 (Supplement): 1–36.

Bernard, V. L., and J. K. Thomas. 1990. Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. *Journal of Accounting and Economics* 13 (4): 305–40.

Badertscher, B., N. Shroff., and H. White. 2013. Externalities of public firm presence: Evidence from private firms' investment decisions. *Journal of Financial Economics* 109 (3): 682-706.

Brown, P. and R. Ball. 1967. Some preliminary findings on the association between the earnings of a firm, its industry, and the economy. *Journal of Accounting Research* (Empirical Research in Accounting: Selected Studies): 55-77.

Chi, S., and D. Shantikumar. 2016. Local bias in Google search and the market response around earnings announcements. *The Accounting Review* 92 (4): 115-143.

Cohen, L., and A. Frazzini. 2008. Economic links and predictable returns. *The Journal of Finance* 63 (4): 1977-2011.

Dereniowski, D., and K. Marek. 2004. Cholesky factorization of matrices in parallel and ranking of graphs. *Lecture Notes on Computer Science.* 3019. Springer-Verlag: 985–992.

Elgers, P., S. Porter, and L, E. Xu. 2008. The timing of industry and firm earnings information in security prices: A re-evaluation. *Journal of Accounting and Economics* 45 (1): 78-93.

Ertimur, Y., J. Livnat, and M. Martikainen. 2003. Differential market reactions to revenue and expense surprises. *Review of Accounting Studies* 8 (2): 185-211.

Foster, G. 1981. Intra-industry information transfers associated with earnings releases. *Journal of Accounting and Economics* 3 (3): 201-232.

Golub, G., and C. Van Loan. 1996. Matrix Computations (3rd ed.). *Baltimore: Johns Hopkins.* Guo, R., B. Lev, and N. Zhou. 2004. Competitive costs of disclosures by Biotech IPOs. Journal of Accounting Research 42 (2): 319-355.

Hanley, K. W., and G. Hoberg. 2010. The information content of IPO prospectus. *The Review of Financial Studies* 23 (7): 2821-2864.

Harford, J. 2005. What drives merger waves? *Journal of Financial Economics* 77 (3): 529-560.

Healy, P., and K. Palepu. 2001. Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of Accounting and Economics* 31 (1): 405-440.

Hirshleifer, D. A., and S. Teoh. 2003. Limited attention, information disclosure, and financial reporting. *Journal of Accounting and Economics* 36 (1): 337-386.

Hirshleifer, D. A., J. N. Myers, L. A. Myers, L. A., and S. H. Teoh. 2008. Do individual investors cause post-earnings announcement drift? Direct evidence from personal trades. *The Accounting Review* 83 (6): 1521-1550.

Hoberg, G., and G. Phillips. 2010. Product market synergies and competition in mergers and acquisitions: A text-based analysis. *Review of Financial Studies* 23 (10): 3773-3811.

Hoberg, G., and G. Phillips. 2016. Text-based network industry classifications and endogenous product differentiation, *Journal of Political Economy* 124 (5) 1423-1465.

Hoberg, G., and G. Phillips. 2017. Text-based industry momentum. Forthcoming at *Journal of Financial and Quantitative Analysis*.

Hui, K. W., and P. Yeung. 2013. Underreaction to industry-wide earnings and the post-forecast revision drift. *Journal of Accounting Research* 51 (4): 701-737.

Hui, K. W., K. K. Nelson, and P. E. Yeung. 2016. On the persistence and pricing of industry-wide and firm-specific earnings, cash flows, and accruals. *Journal of Accounting and Economics* 61 (1): 185-202.

Koh, P-S., and D. M. Reeb. Missing R&D. 2015. *Journal of Accounting and Economics* 60 (1): 73-94.

Kovacs, T. 2016. Intra-industry information transfers and the post-earnings announcement drift. *Contemporary Accounting Research* 33 (4): 1549–1575.

Lansford, B., J. Lee, and J. Tucker. 2008. Disclosure of management guidance in conference calls: Materiality, determinants, and consequences. Northwestern University, Working paper.

Lee, C., P. Ma., and C. Wang. 2015. Search based peer firms: Aggregating investor perceptions through internet co-searches. *Journal of Financial Economics* 116 (2): 410-431.

Livnat, J. 2003. Post-earnings announcement drift: The role of revenue surprises. New York University, Working Paper.

Livnat, J., and R. R. Mendenhall. 2006. Comparing the post–earnings announcement drift for surprises calculated from analyst and time series forecasts. *Journal of Accounting Research* 44 (1): 177-205.

Menzley, L., and O. Ozbas. 2010. Market segmentation and cross-predictability of returns, *The Journal of Finance* 65 (4): 1555-1580.

Ng, J., T.O. Rusticus, and R. S. Verdi. 2008. Implications of transaction costs for the post earnings announcement drift. *Journal of Accounting Research* 46 (3): 661-696.

Pandit, S., C. Wasley., and T. Zach. 2011. Information externalities along the supply chain: The economics determinants of suppliers' stock price reaction to their customers' earnings announcement. *Contemporary Accounting Research* 28 (4): 1304-1343.

Peters, R., and L. Taylor. 2017. Intangible capital and the investment-q relation. *Journal of Financial Economics* 123: 251-272.

Sadka, R. 2006. Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk. *Journal of Financial Economics* 80 (2): 309-349.

Sheen, A. 2014. The real product market impact of mergers. *The Journal of Finance* 69 (6): 2651–2688.

Shroff, N., R. Verdi, and B. Yost. 2017. When does peer information matter? Forthcoming at *Journal of Accounting and Economics*.

Sloan, R., 1996. Do stock prices reflect information in accruals and cash flows about future earnings? *The Accounting Review* 71 (3): 289–315.

Wicklin, R. 2010, 2013. Statistical Programming with SAS/IML Software. SAS Institute.

Appendix A. Variable Definition

Variable	Definition
CAR[X,Y]	= Size and book-to-market adjusted returns accumulated over a window from X calendar days after earnings announcements to Y calendar days after earnings announcements.
SUE	= Standardized unexpected earnings, defined as unexpected earnings (= earnings t – earnings t-4) minus the mean value of past 8 unexpected earnings and scaled by the standard deviation of past 8 unexpected earnings [refer to Bernard and Thomas 1989; Ball and Bartov 1996; Sadka 2006].
$SUE_{Industry}$	= Average standardized earnings surprise of firms included in a given industry. TNIC2⊥3 and SIC2⊥3 denote firms included in TNIC2 and SIC2 but excluded from TNIC3 and SIC3, respectively.
Size	= The natural logarithm of market value of equity.
BTM	= Book-to-market ratio.
Sale	= Standardized unexpected sales, defined as unexpected sales (sales t – sale t-4) minus the mean value of past 8 unexpected sales and scaled by the standard deviation of past unexpected sales.
OIBDP	= Standardized unexpected OIBDP (Operating Income before Depreciation), defined as unexpected OIBDP (OIBDP t – OIBDP t-4) minus the mean value of past 8 unexpected OIBDP and scaled by the standard deviation of past unexpected OIBDP.
OI	= Standardized unexpected OI (Operating Income), defined as unexpected OI (OI t – OI t-4) minus the mean value of past 8 unexpected OI and scaled by the standard deviation of past unexpected OI.
PI	= Standardized unexpected PI (Pre-tax Income), defined as unexpected PI (PI t – PI t-4) minus the mean value of past 8 unexpected PI and scaled by the standard deviation of past unexpected PI.
SupSide	= Standardized unexpected supply side (= COGS + SG&A), defined as unexpected supply side shock (supply $side_t$ – supply $side_{t-4}$) minus the mean value of past 8 unexpected supply side and scaled by the standard deviation of past unexpected supply side shocks.
ResSupSide	= Standardized unexpected residual supply side (= the residual from regressing COGS+SG&A on sales), defined as unexpected residual supply side shock (residual supply $side_t$ – residual supply $side_{t-4}$) minus the mean value of past 8 unexpected residual supply side and scaled by the standard deviation of past unexpected residual supply side shocks.
DemSide	= Standardized demand side (= sales – *ResSupSide*), defined as unexpected demand side shock (demand $side_t$ – demand $side_{t-4}$) minus the mean value of past 8 unexpected demand side and scaled by the standard deviation of past unexpected demand side shocks.
EarnExp	= The sum of earnings before extraordinary items and *ResSupSide*.

Common	= Mutual funds' joint ownership of peer firms in a given industry [see Cohen and Frazzini 2008].

Appendix A. Variable Definition (Continued)

Variable	Definition
TNIC3TSIMM	= Firm-by-firm pairwise total product market similarity based on textual analysis of product descriptions available from 10-K filings [refer to Hoberg and Philips 2016].
SG&A	= Sales, general, and administrative expenses scaled by sales.
Opacity Exp	= Opacity for expense-side disclosures, defined as a text-based opacity measure based on MD&A paragraphs containing expense discussions [see Hanley and Hoberg 2010]. This is scaled by an analogous text-based opacity measure for revenue-side MD&A disclosures as our objective is to measure if the supply side is more opaque than the demand side.

Appendix B. Text-Based Network Industry Classification

Hoberg and Phillips (2016) suggest measuring the extent to which firms relate to others in the product market, by relying on the product market descriptions available from 10-K filings. They determine the relation of these words and produce a relatedness or similarity score for each firm with all other publicly traded firms. This similarity score is a cosine similarity score that evaluates the similarity across documents.

This industry classification considers the possibility that competition may evolve dynamically every year, and is thus more flexible to incorporating business or technical changes in classifying a group of firms as industry peers. Another feature is that it allows each firm to have its own set of distinct competitors. Analogously, this is similar to a social network, where individual (firms) have a distinct set of friends (competitors). This feature is more realistic considering the following example:

Suppose both firm A and B consider firm C as a rival. However, firm A offers products distinct from what firm B offers. In this case, due to product differentiation, firm A and firm B are not in a competitive relationship with each other, although they have a common rival firm C. In general, TNIC reflects the fact that firms that have a common rival do not necessarily compete with each other.

These features enable better identification of industry peers. Hoberg and Phillips (2010; 2017) also show that the use of TNIC product market industry peers instead of to SIC or NAICS generates economically large improvement in explaining competitions and cross-sectional firm characteristics.

Appendix C. Inverse Cholesky Transformation

The Cholesky decomposition states that we can decompose a given positive-definite matrix Σ into a form that satisfies $\Sigma = LL^t$, where L is a lower triangular matrix with positive entries on its diagonals (Golub and Van Loan 1996). In this paper, we rely on the properties of the Cholesky decomposition for two purposes: (1) to uncorrelate a set of variables, and (2) to standardize variables.

In our model, we include a set of earnings surprises, one of which is the focal firm's earnings, two of which are industry level earnings surprises in the product market (one for the closely connected and the other for the remotely connected), and the rest of which are industry level earnings surprises in the traditional industry classification (also one for the closely connected and the other for the remotely connected). As these variables are inherently correlated and overlap with each other, we need to orthogonalize these variables to mitigate the multicollinearity problem. Also, the standardization of our main variables of interest, earnings surprises, will enable a more intuitive interpretation of our results.

We thus use the inverse Cholesky transformation, which uses the Cholesky decomposition on the given covariance matrix to make a linear transformation to (1) uncorrelate and (2) standardize a set of variables at the same time. To implement this transformation, we conduct a cross-sectional (instead of pooled) transformation in each year-quarter to avoid look-ahead bias. We find that, in each year-quarter, the off-diagonal terms of the covariance matrix become (very close to) zero and the diagonal terms become (very close to) one, which is indicative of a successful transformation. Note that, in Table 1, the various SUE variables have nearly identical variance. They are not exactly equal to one due to the fact that we use cross-sectional transformations in each period.

Golub and Van Loan (1996) provide more detailed statistical background and proofs related to the Cholesky decomposition, and Wicklin (2010, 2013) provide the implementation of the inverse Cholesky decomposition in SAS.

Figure 1. Inter-Firm Relations in the Product Market

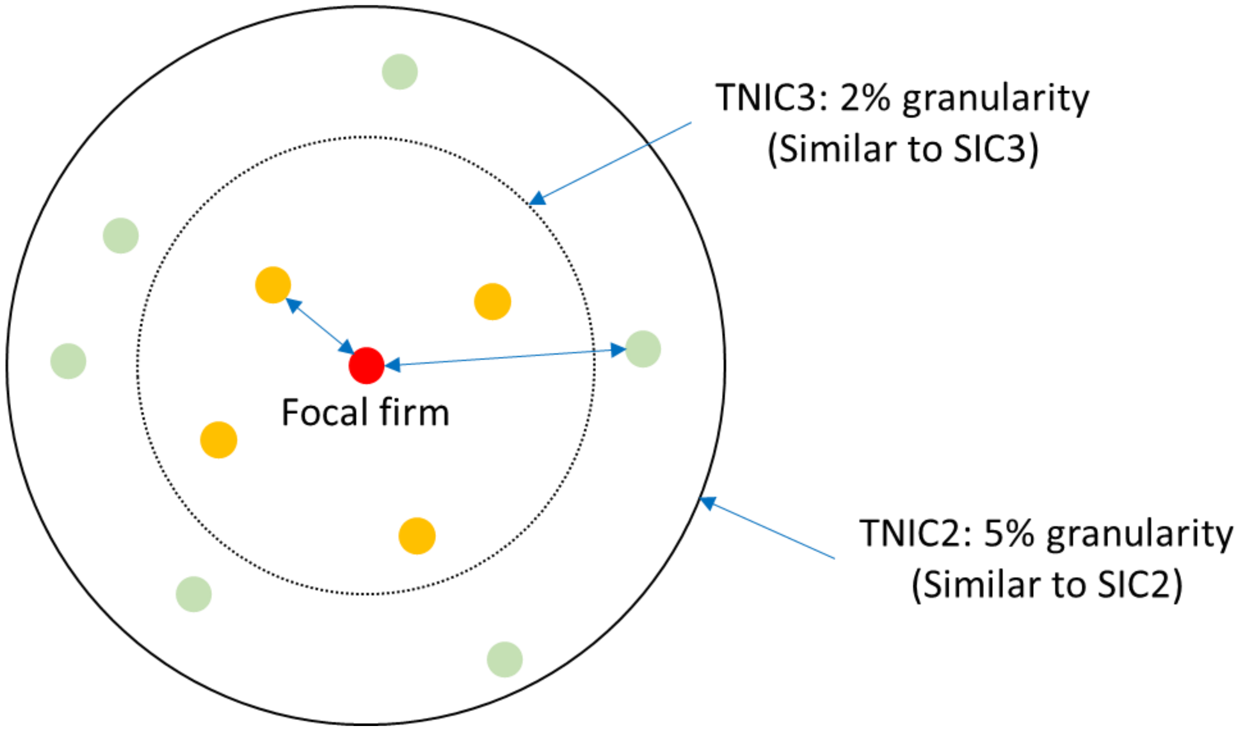
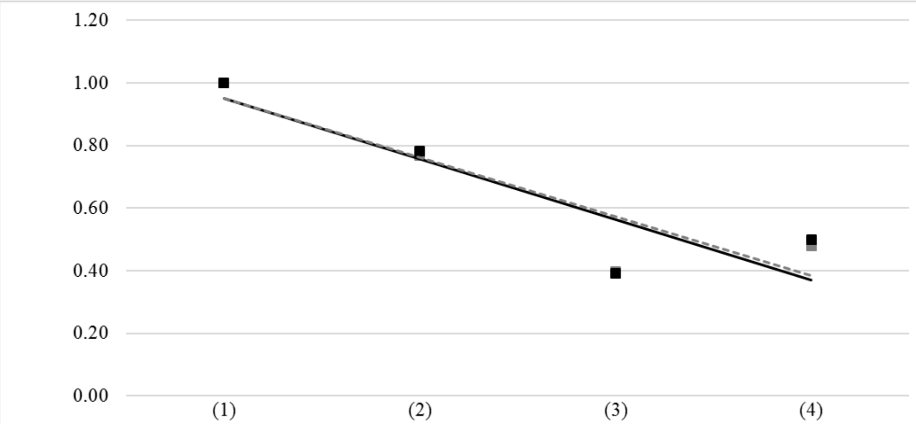


Figure 1 shows an example of a product market space with different granularity. The focal firm at the center has closely linked product market industry peers (TNIC3) in the inner circle, and also remotely linked product market industry peers (TNIC2⊥3) outside the inner circle but inside the outer circle.

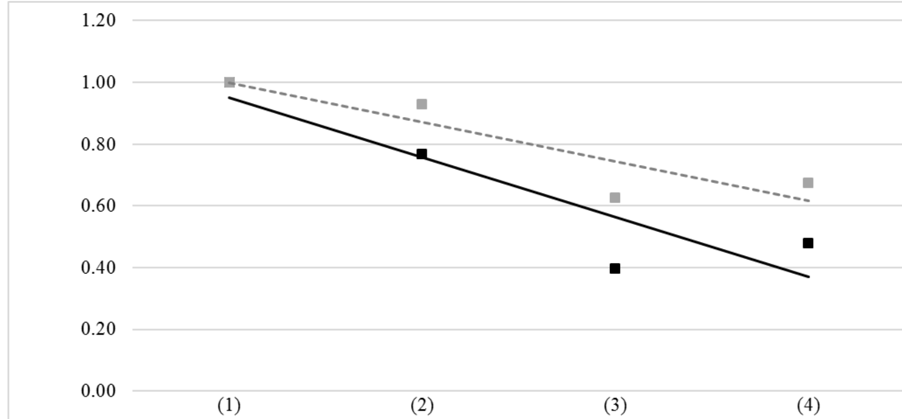
Figure 2. Decay Rate (Duration) of Earnings Surprise Propagation

Panel A. TNIC3 vs. SIC3



	(1)	(2)	(3)	(4)
TNIC3	1.000	0.767	0.397	0.479
SIC3	1.000	0.783	0.391	0.500

Panel B. TNIC3 vs. TNIC2⊥3



	(1)	(2)	(3)	(4)
TNIC3	1.000	0.767	0.397	0.479
TNIC2⊥3	1.000	0.930	0.628	0.674

Figure 2 depicts the decay rate of past SUE's ability to predict current earnings. A slow decay rate would indicate information propagating through the peer network more slowly. The data points in the above figures are from Table 3 and are equal to each quarter's coefficient for each SUE variable divided by the coefficient from the most recent quarter t+1. The decay rate is then indicated by the slope of the regression line (displayed on each graph) running through the four points. A steeper slope indicates more rapid decay. Panel A reports the decay rate using the SUE_{TNIC3} coefficients (TNIC3: solid line) and the SUE_{SIC3} coefficients (SIC3: dotted line). Panel B compares closely connected peers SUE_{TNIC3} (TNIC3: solid line) and remotely connected peers $SUE_{TNIC2\perp3}$ (TNIC2⊥3: dotted line).

Figure 3. Stock Turnover Test

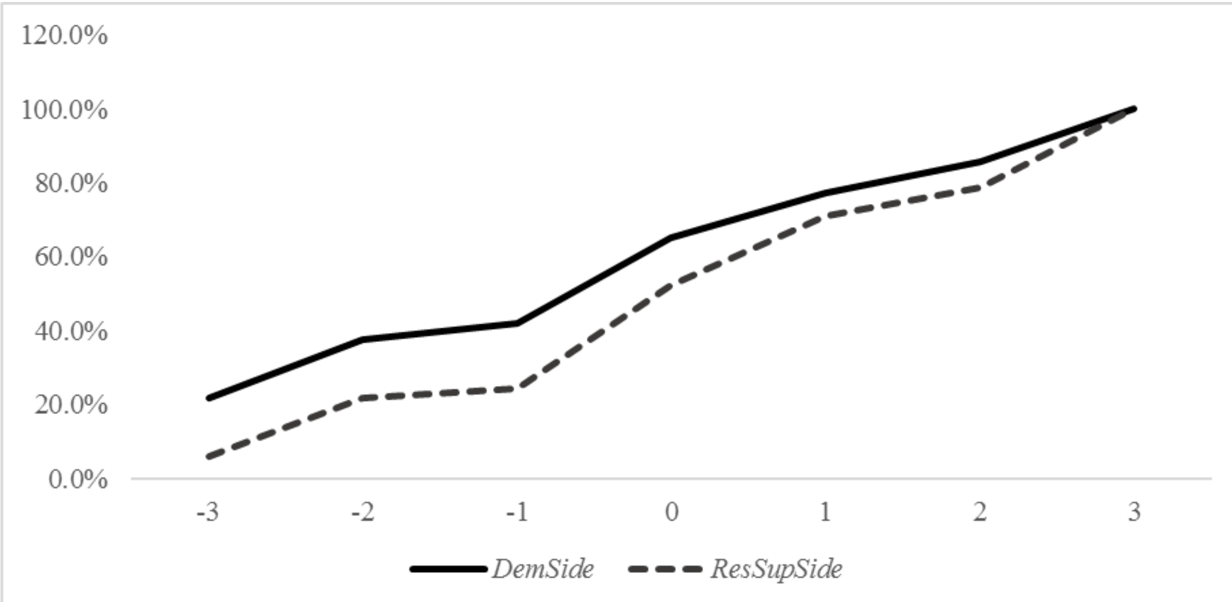


Figure 3 plots monthly stock turnover for the seven month window centered on month zero, the month of a large earnings shock. We compute monthly stock turnover as monthly trading volume divided by shares outstanding. For each firm, we then take the natural log of the given month's turnover divided by the average ex ante average turnover from months t-13 to t-2. On the demand-side (solid line), we then sort stocks into quintiles based on their demand side shock in month zero, and the figure presents the average turnover ratio of the high quintile minus the average turnover ratio of the low quintile (rescaled to units where 100% indicates the ex post turnover relative to the ex ante baseline). The dotted line reports analogous results for high minus low residual supply side shocks.

Table 1. Descriptive Statistics

Variable	N	Mean	Std Dev	25th Pctl	50th Pctl	75th Pctl
CAR[2,90]	202,488	0.002	0.303	-0.132	-0.016	0.101
CAR[2,180]	202,488	0.001	0.469	-0.205	-0.032	0.139
CAR[2,360]	202,488	0.003	0.741	-0.311	-0.066	0.188
SUE	202,488	-0.024	1.010	-0.702	-0.015	0.671
SUE_{TNIC3}	202,488	-0.059	1.061	-0.674	-0.067	0.557
$SUE_{TNIC2\perp3}$	202,488	-0.101	1.131	-0.811	-0.128	0.607
SUE_{SIC3}	202,488	-0.066	1.013	-0.579	-0.066	0.454
$SUE_{SIC2\perp3}$	202,488	-0.087	1.059	-0.568	-0.095	0.430
Size	202,488	5.754	2.075	4.243	5.695	7.147
BTM	202,488	0.733	0.845	0.315	0.545	0.877
Sale	200,345	0.086	1.045	-0.775	0.151	0.937
OIBDP	176,160	0.015	1.011	-0.766	0.036	0.801
OI	171,151	0.003	1.013	-0.782	0.023	0.793
PI	201,996	-0.022	1.011	-0.716	-0.012	0.689
SupSide	160,762	0.096	1.101	-0.805	0.183	0.982
ResSupSide	160,736	0.038	1.061	-0.782	0.045	0.840
DemSide	160,736	0.050	1.092	-0.821	0.109	0.926
EarnExp	160,740	0.006	1.023	-0.632	0.018	0.668
Common	189,760	0.184	0.128	0.081	0.180	0.283
Similarity	202,488	9.472	17.728	1.306	2.378	6.643
SG&A	165,092	1.116	95.200	0.159	0.269	0.409
OpacityExp	187,010	1.099	0.662	0.995	1.025	1.069

Table 1 shows the descriptive statistics of variables used in our analyses. Subscript refers to the industry over which we take the mean of the given variable. Appendix A provides the definition of the variables in detail.

Table 2. Correlation Matrix

Panel A. Market Reaction

	SUE	*SUE*$_{TNIC3}$	*SUE*$_{TNIC2\perp3}$	*SUE*$_{SIC3}$	*SUE*$_{SIC2\perp3}$	*Size*	*BTM*
CAR [2,90]	0.046	0.027	0.015	0.004	-0.007	-0.017	0.025
	<.0001	<.0001	<.0001	0.091	0.003	<.0001	<.0001
SUE		0.049	0.073	0.025	0.044	0.005	-0.011
		<.0001	<.0001	<.0001	<.0001	0.043	<.0001
SUE$_{TNIC3}$			0.172	0.056	0.104	0.002	-0.020
			<.0001	<.0001	<.0001	0.338	<.0001
SUE$_{TNIC2\perp3}$				0.059	0.129	0.000	-0.014
				<.0001	<.0001	0.874	<.0001
SUE$_{SIC3}$					0.039	0.003	-0.006
					<.0001	0.150	0.009
SUE$_{SIC2\perp3}$						0.009	-0.028
						0.000	<.0001
Size							-0.345
							<.0001

Panel B. Income Statement Items

		(2) COGS + SG&A	(3) Operating Income Before Depreciation	(4) Operating Income	(5) Pre-Tax Income	(6) Earnings
(1)	*Revenue*	0.984	0.782	0.718	0.592	0.496
		<.0001	<.0001	<.0001	<.0001	<.0001
(2)	*COGS + SG&A*		0.679	0.609	0.513	0.423
			<.0001	<.0001	<.0001	<.0001
(3)	*Operating Income Before Depreciation*			0.978	0.747	0.657
				<.0001	<.0001	<.0001
(4)	*Operating Income*				0.757	0.677
					<.0001	<.0001
(5)	*Pre-Tax Income*					0.959
						<.0001

Table 2 shows Pearson correlation coefficients with p-values below. Panel A shows the univariate test results of market reaction to earnings surprises. Panel B shows the correlation among various (unstandardized, not seasonally differenced) income statement items. Appendix A provides the definition of the variables in detail.

Table 3. Network Propagation Effect in Earnings through Industry Peers

	SUE_{t+1} (1)	SUE_{t+2} (2)	SUE_{t+3} (3)	SUE_{t+4} (4)
SUE	0.349***	0.185***	0.039***	-0.323***
	(33.833)	(21.137)	(4.841)	(-28.577)
SUE_{TNIC3}	0.072***	0.056***	0.029***	0.035***
	(13.315)	(9.459)	(4.599)	(4.946)
$SUE_{TNIC2\perp3}$	0.043***	0.040***	0.028***	0.030***
	(7.156)	(4.593)	(3.023)	(3.132)
SUE_{SIC3}	0.045***	0.035***	0.018***	0.024***
	(12.365)	(8.136)	(4.006)	(4.947)
$SUE_{SIC2\perp3}$	0.000	-0.007	-0.011*	-0.009
	(0.100)	(-1.366)	(-1.904)	(-1.240)
Size	-0.009**	-0.013***	-0.016***	-0.015***
	(-2.352)	(-2.674)	(-2.933)	(-2.862)
BTM	-0.003	0.035***	0.065***	0.058***
	(-0.355)	(4.330)	(6.699)	(7.826)
Constant	0.035*	0.020	0.002	-0.002
	(1.750)	(0.805)	(0.056)	(-0.066)
Observations	202,488	202,488	202,488	202,488
R-squared	0.131	0.043	0.009	0.101
Clustered by	Firm, Year-Quarter	Firm, Year-Quarter	Firm, Year-Quarter	Firm, Year-Quarter

Table 3 reports the relationship between earnings shocks to industry peers and the focal firm's future earnings surprises over time. We make a distinction between TNIC- and SIC-industry peers as well as more versus less granular industry peers in TNIC- and SIC-industry classification. SUE variables (both firm and industry) are adjusted by the inverse Cholesky decomposition to mitigate multicollinearity in regression. We cluster standard errors by firm and year-quarter and report t-statistics in parentheses. Appendix A provides the definition of the variables in detail.

Table 4. PEAD Regression over Various Windows

Panel A. Overlapping Abnormal Returns

	CAR [2,90] (1)	*CAR [2,180]* (2)	*CAR [2,360]* (3)
SUE	0.012***	0.018***	0.023***
	(8.061)	(7.426)	(7.933)
SUE_{TNIC3}	0.006***	0.013***	0.018***
	(2.836)	(3.824)	(4.229)
$SUE_{TNIC2 \perp 3}$	0.002	0.006	0.010**
	(0.912)	(1.488)	(1.983)
SUE_{SIC3}	0.001	0.002	0.002
	(0.577)	(0.989)	(0.834)
$SUES_{SIC2 \perp 3}$	-0.003	-0.004	-0.004
	(-1.298)	(-1.090)	(-0.917)
Size	0.001	0.001	0.001
	(0.789)	(0.429)	(0.477)
BTM	0.005*	0.009*	0.019*
	(1.803)	(1.671)	(1.845)
Constant	-0.011	-0.016	-0.030
	(-0.944)	(-0.912)	(-1.229)
Observations	202,488	202,488	202,488
R-squared	0.004	0.005	0.004
Clustered by	Firm, Year-Quarter	Firm, Year-Quarter	Firm, Year-Quarter

Table 4. PEAD Regression over Various Windows (Continued)

Panel B. Non-Overlapping Abnormal Returns

	CAR [2,90] (1)	*CAR [91,180]* (2)	*CAR [181,360]* (3)	*CAR [361,720]* (4)
SUE	0.012***	0.005***	0.007***	-0.002
	(8.061)	(3.591)	(4.356)	(-0.793)
SUE_{TNIC3}	0.006***	0.006***	0.006**	0.002
	(2.836)	(2.810)	(2.218)	(0.429)
$SUE_{TNIC2\perp3}$	0.002	0.003	0.006	0.011**
	(0.912)	(1.046)	(1.408)	(2.220)
SUE_{SIC3}	0.001	0.001	0.001	0.002
	(0.577)	(0.882)	(0.479)	(0.588)
$SUES_{SIC2\perp3}$	-0.003	-0.001	-0.001	-0.010*
	(-1.298)	(-0.616)	(-0.302)	(-1.908)
Size	0.001	0.001	0.001	0.003
	(0.789)	(0.626)	(0.290)	(1.366)
BTM	0.005*	0.004	0.008*	0.009*
	(1.803)	(1.234)	(1.796)	(1.791)
Constant	-0.011	-0.009	-0.011	-0.026
	(-0.944)	(-0.901)	(-0.656)	(-1.131)
Observations	202,488	201,897	201,147	199,099
R-squared	0.004	0.002	0.002	0.001
Clustered by	Firm, Year-Quarter	Firm, Year-Quarter	Firm, Year-Quarter	Firm, Year-Quarter

Table 4 shows how investors incorporate earnings shocks to industry peers over various delayed time windows. We use size- and book-to-market adjusted abnormal returns accumulated over specified windows relative to earnings announcements. SUE variables (both firm and industry) are adjusted by the inverse Cholesky decomposition to mitigate multicollinearity in regression. We cluster standard errors by firm and year-quarter and report t-statistics in parentheses. Appendix A provides the definition of the variables in detail.

Table 5. Underlying Mechanisms: Income Statement Items

Panel A. Real-Side

	SUE_{t+1} (1)	SUE_{t+2} (2)	SUE_{t+3} (3)	SUE_{t+4} (4)
$Sale_{TNIC3}$	0.077***	0.076***	0.053***	0.048***
	(10.080)	(6.272)	(3.601)	(3.150)
$Sale_{TNIC2\perp3}$	0.034***	0.042***	0.036**	0.034*
	(3.462)	(2.764)	(2.043)	(1.946)
$OIBDP_{TNIC3}$	0.070***	0.060***	0.037***	0.041***
	(12.068)	(9.359)	(4.774)	(4.986)
$OIBDP_{TNIC2\perp3}$	0.042***	0.039***	0.029***	0.031***
	(6.373)	(4.410)	(3.033)	(3.154)
OI_{TNIC3}	0.072***	0.060***	0.034***	0.038***
	(12.547)	(9.249)	(4.756)	(4.611)
$OI_{TNIC2\perp3}$	0.042***	0.039***	0.026***	0.029***
	(5.941)	(4.127)	(2.809)	(3.163)
PI_{TNIC3}	0.072***	0.057***	0.030***	0.035***
	(13.853)	(9.339)	(4.540)	(4.728)
$PI_{TNIC2\perp3}$	0.043***	0.041***	0.028***	0.031***
	(7.567)	(4.827)	(3.030)	(3.058)
SUE_{TNIC3}	0.072***	0.056***	0.029***	0.035***
	(13.315)	(9.459)	(4.599)	(4.946)
$SUE_{TNIC2\perp3}$	0.043***	0.040***	0.028***	0.030***
	(7.156)	(4.593)	(3.023)	(3.132)

Table 5. Underlying Mechanisms: Income Statement Items (Continued)

Panel B. Financial-Side

	CAR [2,90] (1)	*CAR [2,180]* (2)	*CAR [2,360]* (3)
$Sale_{TNIC3}$	0.002	0.003	0.002
	(0.786)	(0.928)	(0.498)
$Sale_{TNIC2\perp 3}$	-0.000	-0.002	-0.003
	(-0.121)	(-0.381)	(-0.570)
$OIBDP_{TNIC3}$	0.005**	0.010***	0.015***
	(2.183)	(3.209)	(3.563)
$OIBDP_{TNIC2\perp 3}$	0.001	0.002	0.002
	(0.267)	(0.484)	(0.482)
OI_{TNIC3}	0.005**	0.010***	0.016***
	(2.249)	(3.226)	(3.518)
$OI_{TNIC2\perp 3}$	0.001	0.003	0.004
	(0.362)	(0.755)	(0.936)
PI_{TNIC3}	0.007***	0.013***	0.019***
	(2.888)	(3.977)	(4.359)
$PI_{TNIC2\perp 3}$	0.002	0.005	0.009*
	(0.746)	(1.256)	(1.749)
SUE_{TNIC3}	0.006***	0.013***	0.018***
	(2.836)	(3.824)	(4.229)
$SUE_{TNIC2\perp 3}$	0.002	0.006	0.010**
	(0.912)	(1.488)	(1.983)

Table 5 shows the market response to various surprise variables constructed from the income statement in the post-earnings announcement period. We construct firm-level surprise variables using AR (8) and then compute industry-level variables by taking the mean value of the firm-level variable in an industry. AR (8) refers to (1) taking the seasonal difference as a measure of the unexpected firm-level component, then (2) standardizing by subtracting the mean of the unexpected firm-level component over the past eight quarters, and then (3) dividing the standard deviation of the unexpected firm-level component over the past eight quarters. For parsimony, we display TNIC-industry variables only, and do not report the firm-level surprise variable, SIC-industry variables, and controls. Surprise variables (both firm and industry) are adjusted by the inverse Cholesky decomposition to mitigate multicollinearity in regression. We cluster standard errors by firm and year-quarter and report t-statistics in parentheses. Appendix A provides the definition of the variables in detail.

Table 6. Underlying Mechanisms: Supply Shocks

Panel A. Real-Side

	SUE_{t+1} (1)	SUE_{t+2} (2)	SUE_{t+3} (3)	SUE_{t+4} (4)
$SupSide_{TNIC3}$	0.075***	0.070***	0.047***	0.048***
	(8.375)	(5.009)	(2.708)	(2.764)
$SupSide_{TNIC2\perp 3}$	0.045***	0.053***	0.049***	0.050***
	(4.551)	(3.719)	(3.108)	(3.241)
$ResSupSide_{TNIC3}$	0.053***	0.046***	0.026***	0.022***
	(8.931)	(7.681)	(4.105)	(3.902)
$ResSupSide_{TNIC2\perp 3}$	0.035***	0.035***	0.025***	0.027***
	(6.414)	(5.019)	(3.647)	(3.678)
$DemSide_{TNIC3}$	0.075***	0.071***	0.051***	0.048***
	(10.882)	(6.587)	(3.947)	(3.660)
$DemSide_{TNIC2\perp 3}$	0.047***	0.050***	0.036**	0.035***
	(5.361)	(4.082)	(2.533)	(2.628)
SUE_{TNIC3}	0.072***	0.056***	0.029***	0.035***
	(13.315)	(9.459)	(4.599)	(4.946)
$SUE_{TNIC2\perp 3}$	0.043***	0.040***	0.028***	0.030***
	(7.156)	(4.593)	(3.023)	(3.132)
$EarnExp_{TNIC3}$	0.058***	0.042***	0.022***	0.027***
	(10.687)	(8.095)	(4.033)	(5.107)
$EarnExp_{TNIC2\perp 3}$	0.039***	0.033***	0.020**	0.024***
	(7.590)	(4.719)	(2.433)	(3.149)

Table 6. Underlying Mechanisms: Supply Shocks (Continued)

Panel B. Financial-Side

	CAR [2,90] (1)	*CAR [2,180]* (2)	*CAR [2,360]* (3)
$SupSide_{TNIC3}$	0.001	0.001	-0.001
	(0.222)	(0.244)	(-0.337)
$SupSide_{TNIC2\perp3}$	-0.001	-0.002	-0.007
	(-0.181)	(-0.470)	(-1.096)
$ResSupSide_{TNIC3}$	0.006***	0.012***	0.019***
	(2.765)	(3.997)	(4.273)
$ResSupSide_{TNIC2\perp3}$	0.004	0.009**	0.014***
	(1.442)	(2.319)	(2.842)
$DemSide_{TNIC3}$	0.002	0.004	0.006
	(0.813)	(1.237)	(1.279)
$DemSide_{TNIC2\perp3}$	-0.001	-0.001	-0.003
	(-0.298)	(-0.380)	(-0.782)
SUE_{TNIC3}	0.006***	0.013***	0.018***
	(2.836)	(3.824)	(4.229)
$SUE_{TNIC2\perp3}$	0.002	0.006	0.010**
	(0.912)	(1.488)	(1.983)
$EarnExp_{TNIC3}$	0.002	0.003	0.004
	(0.923)	(0.880)	(0.868)
$EarnExp_{TNIC2\perp3}$	0.002	0.005	0.006
	(0.608)	(0.857)	(1.005)

Table 6 shows the market response to residual demand and supply variables constructed from the income statement in the post-earnings announcement period. We construct firm-level surprise variables using AR (8) and then compute industry-level variables by taking the mean value of the firm-level variable in an industry. AR (8) refers to (1) taking the seasonal difference as a measure of the unexpected firm-level component, then (2) standardizing by subtracting the mean of the unexpected firm-level component over the past eight quarters, and then (3) dividing the standard deviation of the unexpected firm-level component over the past eight quarters. For parsimony, we display TNIC-industry variables only and do not report firm-level surprise variable, SIC-industry variables, and controls. Surprise variables (both firm and industry) are adjusted by the inverse Cholesky decomposition to mitigate multicollinearity in regression. We cluster standard errors by firm and year-quarter and report t-statistics in parentheses. Appendix A provides the definition of the variables in detail.

Table 7. Cross-sectional test: SG&A - Lowest vs. Highest Quintile

Panel A. SG&A Ratio Quintiles

	CAR[2,90]		*CAR[2,180]*		*CAR[2,360]*	
	Low	High	Low	High	Low	High
SUE	0.012***	0.014***	0.014***	0.025***	0.012*	0.042***
	(4.073)	(4.381)	(2.993)	(4.770)	(1.645)	(4.696)
SUE_{TNIC3}	0.001	0.016***	0.002	0.033***	0.002	0.059***
	(0.462)	(2.739)	(0.599)	(3.686)	(0.339)	(3.733)
$SUE_{TNIC2\perp 3}$	-0.003	0.011	-0.002	0.027**	-0.000	0.052***
	(-0.789)	(1.643)	(-0.487)	(2.390)	(-0.008)	(2.704)
SUE_{SIC3}	0.001	0.002	0.001	0.004	-0.000	0.014
	(0.382)	(0.452)	(0.463)	(0.738)	(-0.057)	(1.193)
$SUE_{SIC2\perp 3}$	-0.005***	0.002	-0.007**	0.004	-0.012**	0.017
	(-2.618)	(0.198)	(-2.218)	(0.379)	(-2.276)	(0.979)
Size	-0.000	-0.001	-0.002	-0.001	-0.003	-0.001
	(-0.271)	(-0.397)	(-0.789)	(-0.362)	(-0.736)	(-0.170)
BTM	0.005	0.015*	0.011	0.026*	0.015	0.066**
	(0.925)	(1.795)	(0.899)	(1.868)	(0.659)	(2.186)
Constant	0.004	-0.016	0.012	-0.030	0.028	-0.055
	(0.332)	(-0.732)	(0.624)	(-0.903)	(0.749)	(-1.184)
Observations	33,043	32,998	33,043	32,998	33,043	32,998
R-squared	0.004	0.008	0.004	0.016	0.002	0.026
Clustered by	Firm, Year-Quarter	Firm, Year-Quarter	Firm, Year-Quarter	Firm, Year-Quarter	Firm, Year-Quarter	Firm, Year-Quarter

Table 7. Cross-sectional test: SG&A - Lowest vs. Highest Quintile (Continued)

Panel B. Expense Disclosure Opacity Quintiles

	CAR[2,90]		*CAR[2,180]*		*CAR[2,360]*	
	Low	High	Low	High	Low	High
SUE	0.014***	0.014***	0.018***	0.025***	0.023***	0.039***
	(6.969)	(7.037)	(6.159)	(8.301)	(4.498)	(7.863)
SUE_{TNIC3}	0.006**	0.013***	0.011***	0.027***	0.012**	0.039***
	(2.347)	(3.760)	(2.632)	(5.122)	(2.481)	(5.003)
$SUE_{TNIC2\perp3}$	0.002	0.004	0.006	0.008	0.009	0.014*
	(0.671)	(1.367)	(1.221)	(1.599)	(1.609)	(1.857)
SUE_{SIC3}	-0.002	0.003	-0.002	0.006	-0.002	0.010
	(-0.915)	(0.840)	(-0.809)	(1.271)	(-0.468)	(1.531)
$SUE_{SIC2\perp3}$	-0.002	-0.004	-0.004	-0.004	-0.004	-0.004
	(-1.135)	(-1.328)	(-1.268)	(-0.903)	(-0.774)	(-0.584)
Size	0.001	0.000	0.001	0.000	0.003	0.000
	(0.522)	(0.286)	(0.428)	(0.019)	(0.858)	(0.009)
BTM	0.006	0.001	0.016	0.003	0.029*	0.015
	(1.375)	(0.286)	(1.396)	(0.427)	(1.755)	(1.252)
Constant	-0.007	-0.011	-0.017	-0.017	-0.041	-0.038
	(-0.522)	(-0.856)	(-0.716)	(-0.890)	(-1.266)	(-1.128)
Observations	37,426	37,382	37,426	37,382	37,426	37,382
R-squared	0.005	0.006	0.005	0.010	0.005	0.011
Clustered by	Firm, Year-Quarter	Firm, Year-Quarter	Firm, Year-Quarter	Firm, Year-Quarter	Firm, Year-Quarter	Firm, Year-Quarter

Table 7. Cross-sectional test: SG&A - Lowest vs. Highest Quintile (Continued)

Panel C. Two-Way Sorts by SG&A Ratio and Expense Opacity

CAR[2,360], SUE_{TNIC3}		*OpacityExp*		
		Low	Middle	High
SG&A	Low	0.005	-0.000	0.009
		(1.019)	(-0.011)	(1.188)
	Middle	0.005	0.018***	0.021**
		(0.890)	(2.991)	(2.142)
	High	0.039***	0.040***	0.065***
		(3.363)	(3.458)	(4.098)

Table 7 shows cross-sectional tests with partitions based on the SG&A ratio (SG&A/sales) and expense disclosure opacity, which is computed using expense discussions in the MD&A section of the 10-K. In Panel A (Panel B), we partition samples into quintiles in each year based on the SG&A ratio (MD&A expense disclosure opacity), and run the market reaction regressions in each subsample. In Panel C, we consider two-way sorts into terciles in each year based on the SG&A ratio and expense disclosure opacity. We use size- and book-to-market adjusted abnormal returns accumulated over specified windows relative to earnings announcements. SUE variables (both firm and industry) are adjusted by the inverse Cholesky decomposition to mitigate multicollinearity in regression. We cluster standard errors by firm and year-quarter and report t-statistics in parentheses. Appendix A provides the definition of the variables in detail.

Table 8. Cross-sectional test: Mutual Fund Ownership - Lowest vs. Highest quintile

	CAR[2,90]		*CAR[2,180]*		*CAR[2,360]*	
	Low	High	Low	High	Low	High
SUE	0.018***	0.010***	0.030***	0.011***	0.041***	0.012**
	(10.466)	(3.772)	(12.061)	(2.809)	(10.217)	(2.163)
SUE_{TNIC3}	0.010***	0.002	0.017***	0.006	0.020***	0.008
	(3.959)	(0.597)	(4.886)	(1.471)	(3.963)	(1.429)
$SUE_{TNIC2\perp3}$	0.001	0.002	0.007	0.003	0.012	0.003
	(0.559)	(0.631)	(1.469)	(0.562)	(1.596)	(0.568)
SUE_{SIC3}	0.004	-0.001	0.008**	0.000	0.016***	-0.001
	(1.429)	(-0.529)	(1.969)	(0.126)	(2.643)	(-0.288)
$SUE_{SIC2\perp3}$	-0.002	-0.003	-0.003	-0.002	-0.008	-0.001
	(-0.556)	(-1.470)	(-0.656)	(-0.584)	(-1.044)	(-0.135)
Size	0.002	-0.010**	0.003	-0.018*	0.008*	-0.026*
	(1.293)	(-1.963)	(1.275)	(-1.943)	(1.897)	(-1.797)
BTM	0.003	0.004	0.008	0.003	0.021**	-0.006
	(1.072)	(0.460)	(1.612)	(0.230)	(2.039)	(-0.280)
Constant	-0.017	0.064*	-0.033*	0.113*	-0.073***	0.164*
	(-1.420)	(1.745)	(-1.839)	(1.734)	(-2.871)	(1.654)
Observations	38,839	37,932	38,839	37,932	38,839	37,932
R-squared	0.006	0.004	0.009	0.004	0.008	0.003
Clustered by	Firm, Year-Quarter	Firm, Year-Quarter	Firm, Year-Quarter	Firm, Year-Quarter	Firm, Year-Quarter	Firm, Year-Quarter

Table 8 shows cross-sectional tests with partitions based on mutual funds' joint ownership of peer firms in a given industry. We partition samples into quintiles each year based on the percentage of mutual funds' joint holdings, and run the market reaction regressions in subsamples. We use size- and book-to-market adjusted abnormal returns accumulated over specified windows relative to earnings announcements. SUE variables (both firm and industry) are adjusted by the inverse Cholesky decomposition to mitigate multicollinearity in regression. We cluster standard errors by firm and year-quarter and report t-statistics in parentheses. Appendix A provides the definition of the variables in detail.

Table 9. Cross-sectional test: TNIC Similarity - Lowest vs. Highest quintile

	CAR[2,90]		*CAR[2,180]*		*CAR[2,360]*	
	Low	High	Low	High	Low	High
SUE	0.015***	0.023***	0.020***	0.042***	0.019***	0.057***
	(7.628)	(4.234)	(6.678)	(5.031)	(4.439)	(4.582)
SUE_{TNIC3}	0.002	0.028**	0.004	0.066***	0.006	0.091***
	(0.821)	(2.315)	(1.191)	(3.583)	(1.393)	(2.988)
$SUE_{TNIC2\perp3}$	0.002	-0.006	0.005	-0.017*	0.006	-0.021
	(0.669)	(-0.904)	(1.368)	(-1.847)	(1.118)	(-1.444)
SUE_{SIC3}	0.000	-0.003	0.001	-0.012	-0.001	-0.012
	(0.009)	(-0.392)	(0.469)	(-1.178)	(-0.417)	(-0.831)
$SUE_{SIC2\perp3}$	-0.002	-0.003	-0.007	-0.004	-0.014**	-0.000
	(-0.675)	(-0.385)	(-1.251)	(-0.326)	(-2.168)	(-0.013)
Size	0.003***	-0.001	0.006***	-0.004	0.011***	-0.007*
	(2.623)	(-0.676)	(3.006)	(-1.601)	(2.851)	(-1.853)
BTM	0.006*	-0.004	0.013*	-0.017	0.026*	-0.016
	(1.665)	(-0.515)	(1.863)	(-1.347)	(1.872)	(-0.845)
Constant	-0.025**	0.008	-0.050***	0.027	-0.091***	0.029
	(-2.302)	(0.508)	(-3.093)	(1.337)	(-3.202)	(1.063)
Observations	40,521	40,481	40,521	40,481	40,521	40,481
R-squared	0.005	0.010	0.006	0.018	0.004	0.017
Clustered by	Firm, Year-Quarter	Firm, Year-Quarter	Firm, Year-Quarter	Firm, Year-Quarter	Firm, Year-Quarter	Firm, Year-Quarter

Table 9 shows cross-sectional tests with partitions based on product market similarity. We partition samples into quintiles each year based on product market similarity, and run the market reaction regressions in subsamples. We use size- and book-to-market adjusted abnormal returns accumulated over specified windows relative to earnings announcements. SUE variables (both firm and industry) are adjusted by the inverse Cholesky decomposition to mitigate multicollinearity in regression. We cluster standard errors by firm and year-quarter and report t-statistics in parentheses. Appendix A provides the definition of the variables in detail.